The generation game

Evaluating, buying or selling portfolios of generation assets has always been done in two steps covering engineering and financial analysis. Now there is a single model that combines the two **By Arthur Breipohl, Fred Lee and Qibei Feng**

Evaluation of generation assets, whether for asset-backed deals, for leases or for portfolio sales, has always been done in two separate steps – through engineering analysis and financial analysis. But this article describes a new, single model, called EFR – engineering-financial risk – which combines these two functions, and is more accurate.

In the traditional two-step approach, the first step is an engineering evaluation, which appraises the present value of the income stream using predicted values of the market for electrical energy and ancillary services; the fuel market and a production cost simulation programme. The result of this first step is often called the intrinsic value of the asset. Next, a financial analysis considers market uncertainty together with a cursory model of the generator's optionality – which in this case refers to the ability of a control centre to turn off a generator when prices are too low – and estimates the expected extrinsic value together with some measure of value at risk (Var).

We have designed a two-stage simulation to capture the operation of the portfolio and the uncertainty in prices, quantity of full-service contracts and generation availability.

The first stage uses the optimisation tool GenTrader, which is widely used by traders and asset managers as a stand-alone product. GenTrader optimises the hourly exercise of physical and financial options to maximise profit for a number of deterministic scenarios created by EFR. The optimisation process uses hourly market price curves for energy, ancillary services and fuels. It commits and dispatches generation units, and exercises long and short positions in forward and option contracts.

This optimisation is accomplished under fuel, emission and transmission constraints.

When the first stage of the model is finished, it has created a discrete 'map' of the optimum portfolio and the resulting profit for the chosen scenarios. The scenarios are chosen to cover all the possible outcomes as determined by volatilities of prices, time between the present and the time of operation, the quantities of electricity products, and the availabilities of assets.

The second stage of EFR is based on Monte Carlo sampling, whereas the first step is a series of GenTrader simulations, which are run to determine operational profit for varying market, quantity, and availability conditions.

These simulations cover all the possible outcomes as determined by volatilities of prices, time between the present and the time of operation, variance of the contract quantities and availability rates – the 'sample space'. From the results of the first stage, the partial derivatives, or 'deltas' of the profit portfolio – the rate of change of profit when only one of the risk drivers is changed – with respect to each of the risk drivers is estimated at a number of locations within the sample space. These deltas are then used to form a describing function that represents profit over the simulation horizon as a function of the uncertain, or stochastic, variables. Finally, Monte Carlo simulation is used to estimate the distribution of profit.

The random samples of each stochastic variable are taken on an hourly basis, and these samples can be independent or correlated. Samples from different stochastic processes also can be correlated. Samples for hourly prices are based on a standard geometric Brownian motion model, which results in lognormal random variables with different hourly mean values, while quantities are assumed to come from a Gaussian stochastic process. Generating unit availabilities and transmission path availabilities are chosen from Bernoulli distributions to give the results of the random variables in terms of two possible outcomes – success and failure. The final result is a histogram that estimates the distribution of profit over the simulation horizon, from which expected profit and comprehensive risk measures are evident.

We show the application of this model through examples designed to confirm its capability, starting with a case where the results can be duplicated with a closed form model through examples that are unpredictable by simpler models.

The general conditions for all the examples are as follows:

There are two generators, each of 200 megawatts (MW), that have identical average full-load heat-rates of 10 million British thermal units per megawatt hour (mmBtu/MWh). The first of these two is flexible – that is to say, it has short minimum up-times and down-times, no start-up costs, and a large – 100 MW – spinning reserve capability. The second

Figure 1: Profit of 200MW flexible unit

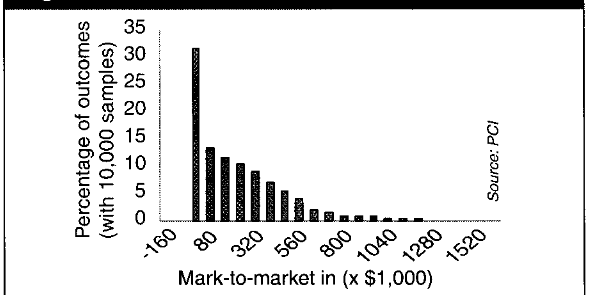

Figure 2: Expected profit for generators vs volatility

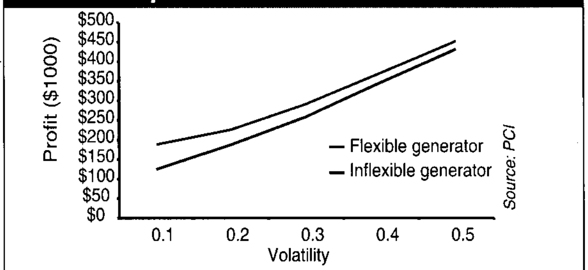

Table 1: Results

Example number	Volatility Energy	Fuel	Reserve	Correlation	Generating unit	Forced outage rate	Profit Mean	Standard dev
1	20%	none	–	–	Flexible	none	$227,223	$259,757
2	20%	none	–	–	Inflexible	none	$186,153	$251,816
4	20%	20%	–	0	Flexible	none	$294,965	$154,272
4	20%	20%	–	0	Inflexible	none	$272,046	$156,570
5	20%	20%	–	0.8	Flexible	none	$276,755	$104,499
5	20%	20%	–	0.8	Inflexible	none	$257,191	$115,510
6	20%	20%	30%	0	Flexible	none	$589,199	$178,574
6	20%	20%	30%	0	Inflexible	none	$512,069	$182,404
7	20%	20%	30%	0	Flexible	0.2	$472,879	$197,152
7	20%	20%	30%	0	Inflexible	0.2	$405,525	$195,341

generator is called inflexible because it has a minimum up-time of six hours and a minimum down-time of 12 hours, only 50 MW of spinning reserve capability and a start-up cost of $1,000.

FLEXIBLE GENERATOR WITH CALL OPTION.

In this first example, the flexible 200 MW generator is analyzed with EFR. The purpose is to demonstrate the results of applying EFR to a totally flexible generator. In this example, the results from our model are equivalent to those obtained from Black's evaluation of a call option.

The example consists of evaluating the generator at present-value time, December 31, 1999, in a market with expected prices of $23/MWh and $15/MWh on-peak and off-peak, respectively, during December 2000. The fuel price is $2/mmBtu, and together with a heat rate of 10 mmBtu/MWH the generator is equivalent to a strike price of $20/MWh for a call option.

At the expected prices, the 200 MW generator will operate for the 16 on-peak hours during the 21 weekdays during December. Thus, for peak hours, we expect the generator to have a mean profit of 200 x 16 x 21 x (call option value) = 67200 x (call option value). The call option value, with T–t = 11.5/12, volatility = 20%, strike price = $20, forward price = $23, and risk-free interest rate = 9% is, using Black's model, $3.288. Thus the expected profit for this generator during on-peak hours is 67200 x 3.288 = $220,954.

The value from a similar calculation for the 408 off-peak hours results in an expected profit of $7,948 for a total expected profit of $228,902. The mean of the EFR simulation results shown in Figure 1 is $227,223. The difference is less than one sample standard deviation of the mean $2,598 and thus is well within sampling error. Note that the information in Figure 1 includes not only the expected value, but also a good estimate of the variation in profit that can be converted to the Var measure of choice. For example, in Figure 1, there is a 31% probability of a mark-to-market value of $0.

THE EFFECT OF PHYSICAL CONSTRAINTS

A standard financial model could have produced the expected value of profit shown in the first example. In this second example, we compare the expected profit from the ideal generator with the second generator, which has more physical constraints. Because its minimum down time is 12 hours, it either cannot reap the potential profit during all of the 16 hours of higher prices, or it must remain on all hours of the weekday and suffer some loss during the eight hours of lower prices.

The optimum trade-off in this situation varies as the prices vary, and this decision requires unit commitment. In this case, the mean profit is reduced from $227,223 to $186,153 because of the scheduling constraints of this inflexible generator. The standard deviation of profit is approximately the same for both generators.

The third example uses the same conditions as in the first two examples. The volatility is now varied from 10% to 50% in 10% steps. Figure 2 shows that while the flexible generator is more profitable than the inflexible one, the gap narrows slightly at higher volatilities, which we attribute to the fact that both generators remain off at very low prices, and both remain on at very high prices. Because there is more optionality, the expected profit of both generators increases with increasing volatility.

POWER AND FUEL PRICE UNCERTAINTY

This example continues the conditions of the earlier examples and adds uncertainty to the fuel market. The fuel market and the power market both have volatilities of 20%. In this example these prices are assumed to be independent.

The results of this simulation are: for the flexible generator, the mean profit is $294,965 and the standard deviation is $154,272; for the inflexible generator, the mean profit is $272,046 and the standard deviation is $156,570. These are approximately the same results shown in Figure 2 with a volatility of 20% in power price only. Figure 3 shows the effect of the two volatilities.

POWER AND FUEL PRICE CORRELATION

In the fifth example, a correlation coefficient of +0.8 is assigned between the logarithm of the ratio of prices in two adjoining periods of power price and fuel price. The positive correlation reduces the mean profit to $276,755 and the standard deviation to $104,499 for the flexible generator.

For the inflexible unit, the mean profit is $257,191 and the standard deviation is $115,510. Positive correlation reduces the means and the standard deviations because changes in energy and fuel prices have opposite effects on profit – that is, the deltas have different signs.

POWER PLUS RESERVE MARKET

The sixth example has a time-varying energy market as shown in Figure 4 and a reserve market of $20/MW during hours 12 through 18 of weekdays. These figures show mean weekly prices, which are repeated for each week during the month of December.

With these prices, the schedule of energy sales is shown in Figure 5. The dip in energy production that occurs in the middle of each weekday is due to the fact that it is more economical to serve the reserve market than to serve the energy market. When the volatility of both fuel and energy prices is 20% and the volatility of reserve prices is 30%, the results of EFR are shown along with a summary of earlier examples in Table 1.

FORCED OUTAGES OF UNITS

The final example continues the same conditions as the previous one, and introduces forced outage rates of 0.2 to each unit. The results are shown in Table 1. Note that the expected profit for each unit is approximately 0.8 times the results of example six.

We have demonstrated a model that shows the effects of engineering parameters – minimum up- and down-times, start-up costs, reserve limitations, forced outage rates – together with financial parameters – mean prices, volatilities, and correlations between prices.

The model estimates the distribution of profit, and this distribution results in a mean and standard deviation. In addition, if the firm uses a Var that is based on a maximum risk at a certain probability, then this Var can be extracted directly from the estimated distribution. The accuracy of the model is demonstrated by comparing results with Black's model in the very simple example.

In addition, it was demonstrated that the model could handle a variety of complications. For example, these include time-varying expected energy prices together with reserve prices, and forced outages of units. ■

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Figure 3: Relative contribution to standard deviation

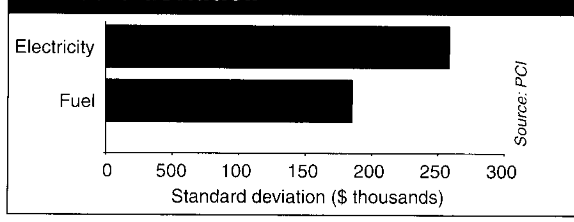

Figure 4: Varying energy market

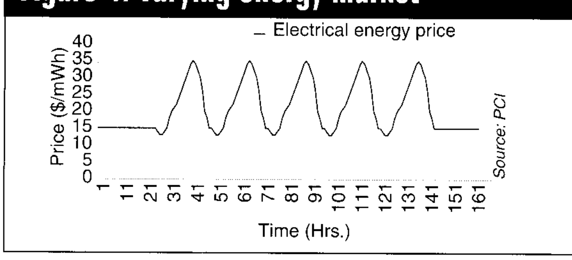

Figure 5: Energy sales